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Assessing the value of museums with a combined discrete choice / count data model

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Abstract
This paper assesses the value of Dutch museums using information about destination choice as well as about the number of trips undertaken by an actor. Destination choice is analyzed by means of a mixed logit model, and a count data model is used to explain trip generation. We use a utility-consistent framework in which the discrete choice model for destination choice is linked to an indirect utility function. The results are used to compute the compensating variation of particular museums and of the total group of museums in the sample.

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1 Introduction

Museums, theaters, recreation sites, or nature reserves often rely on government funding, as they are valued by the population but unable to survive in an open market. Such government funding is believed justified as long as its level does not exceed the total value the population adheres to such collective goods. As the services provided by these amenities are not traded in an open market, standard methods cannot be used to determine their value. Ever since Hotelling suggested the 'travel cost method' in 1947, transportation costs have been used in economics to assess the value of location-specific services. The essential idea is that the travel cost can be interpreted as the price of using the facility and that the demand function can be obtained by plotting the number of visitors as a function of their distance to the facility. The empirical demand function may then be used as the basis for welfare calculations. The travel cost method was further developed and refined in the 1950s and 1960s by Clawson (1959) and Clawson and Knetsch (1966), among others. In the 1970s the economic analysis of discrete choice (see McFadden 1974, 1981), enabled researchers to analyze a trip to a particular facility as the best choice among a number of alternatives that are explicitly taken into account. The next and most recent improvement of the travel cost method is the model of Hausman, Leonard and McFadden (1995) that covers trip generation as well as destination choice in a single utility maximizing framework. The method proposed by Hausman, Leonard and McFadden (HLM) is a major step forward. Its significance is not confined to applications of the travel cost method, but extends to the field of transportation economics, where trip generation and trip distribution tend to be studied separately. However, it will be shown in this paper that a problem is associated with the use of the logit model (and generalizations like the nested logit) in the HLM framework. Moreover, an inherent limitation of their method is that effects of income on destination choice are excluded. For these reasons, we propose an alternative. Like HLM, we use a logit model for destination choice and integrate it with a count data model for the number of trips. However, whereas the HLM framework is based on separability of the *direct* utility function, our approach assumes separability of the *indirect* utility function. We show that the logit model for destination choice fits naturally in this framework and that effects of income on destination choice can be incorporated. The model we develop is consistent with the determination of the number of trips and destination choice as two stages in a utility maximizing planning procedure, just as the one proposed by HLM. Also, empirical implementation can start with estimating the sub-model that explains destination choice and the results can be used in estimating the count data model for trip generation in a second stage of the estimation process. In the discrete choice/count data model developed in this paper the total change in welfare that results from disappearance of a facility is (apart from special cases) a nonlinear function of the change in the logsum. In our model the change in the logsum can be interpreted as the approximation of the welfare effect that results from ignoring the substitution between museum trips and other commodities and is therefore biased upward.

We demonstrate the alternative model in an application of museum visiting. So far the use of travel-cost based procedures to determine the value of cultural goods has been limited. To our knowledge, there have been three applications of demand functions based on travel costs. Forrest, Grime and Woods (2000), and Poor and Smith (2004) show that the use value of, respectively, a local theater and a heritage site alone exceed public funding. Martin (1994) uses travel costs as part of assessing the overall value of a local museum, whereby non use value is determined through Contingency Valuation. Rather than determining the value of a single cultural institution or site, Boter, Rouwendal and Wedel (2005) show how multiple museums may be compared by the different willingness to travel of their visitors. They use a discrete choice approach, employing information on destination choice only. Heterogeneity among consumers is taken into account by means of five latent classes of consumers and there is no welfare analysis, only a comparison of the estimated attractiveness of the museums. In the empirical work in this paper we use a full-fledged discrete choice/count data approach. Moreover, we account for heterogeneity among the decision makers by adopting a mixed logit approach. Our mixed logit destination choice model implies that the logsum, which is the welfare indicator related to destination choice, is a random variable. Since the logsum plays a role in the count data model, this randomness has to be taken into account in estimating the latter model.

2 The two-stage budgeting model

2.1 Introduction

Much travel behavior has at least two aspects: how many trips to make and which destination to choose on each trip. In transportation analysis these two aspects are often described as, respectively, trip generation and trip distribution and the two tend to be studied relatively independent of each other. The separation between these two aspects is more or less analogous to the two stage budgeting procedure in applied consumer theory. Two-stage budgeting allows a researcher to study the determination of the budget for expenditure on a group of commodities (for instance, those to be bought during a particular period) separately from the way this budget is distributed over particular commodities. It was studied first by Strotz (1957) and Gorman (1959) and makes use of the notion of (weak) separability of the utility function. Conventional applications concern commodities that are available in continuous quantities, but HLM (1995) recently employed it also for a commodity that can only be consumed in discrete (integer) units, viz. the number of visits to recreational sites. In the present section we will discuss their method. We point out a difficulty associated with HLM's approach and show that it can be avoided by an alternative approach, which is based on the notion of indirect separability, i.e. weak separability of the indirect utility function. The alternative approach provides a similar justification for the dichotomy between trip generation and trip distribution as that used by HLM. Moreover, empirical implementation of this alternative procedure can proceed along the same lines as that of HLM.

2.2 The method of Hausman, Leonard and McFadden

HLM propose a two-stage procedure that starts from a direct utility function in which a group of goods is separable from the other goods. In the empirical application of the present paper, the relevant group would be museum visits, to be denoted with a suffix *M*. For concreteness, we will always refer to the separable group of commodities as museum trips, although it should be obvious that the discussion may refer to any separable group of commodities. This function can be written as:

$$u = u(x, U_M(q)) \tag{1}$$

where u denotes total utility, x the vector of all other commodities than museum visits and U the group utility function referring to such visits. This function is maximized under a budget constraint:

$$px + \pi q = y\,. \tag{2}$$

where p denotes the prices of other commodities, π the prices of museum visits and y the consumer's budget.

Utility function (1) is an example of a separable utility function. In particular, the commodity group 'museum visits' is separable from the other commodities in this utility function. This separability is apparent from the structure of *u*: the museum visits appear in this function through a group utility function U_M. In general, it is meaningless to speak of the utility of a group of commodities, but if the group is separable from other commodities, it is.[1] Separability of a group of commodities implies that the optimal allocation of resources within the group can be determined on the basis of the group utility function, once the budget that is available for the group and the prices of the commodities within the group are known. If the budget available for museum trips is y_M, the number of trips to each destination can be determined by maximizing the group utility function $U_M(q)$, subject to the constraint that $\pi q = y_M$.

This observation lead Strotz (1957) to the idea that separable utility functions could be used to simplify the consumer's allocation problem. If all commodities belong to mutually disjunct groups and the consumer's utility function is separable in these groups, then the total budget could first be divided into group budgets, and the group budgets could subsequently be allocated over the individual commodities in the groups. This is the basic idea of two-stage budgeting. Gorman (1959) observed that such a two-stage budgeting procedure would be especially useful if the first stage (in which the total budget is divided into group budgets) could be carried out without detailed information about the prices of all commodities within the various groups and pointed out that separability of the utility function was in general not sufficient to enable this simplification. He showed that information about a single (scalar) price index for each group was sufficient under two conditions: either (a) the utility function *u* must be additive in the group utility functions, whereas these group utility functions satisfy a particular functional form that came to be known as Gorman's polar form or (b) the group utility functions are homothetic.

HLM refer to this result and assume that the indirect group utility function corresponding to U_M satisfies the Gorman polar form. This means that the indirect utility function corresponding with U_M, which will be denoted as V_M, can be written as:

$$V_M(y_M, \pi) = \frac{y_M}{b(\pi)} + a(\pi) \tag{3}$$

where $b(.)$ must be homogeneous of degree 1 and $a(.)$ must be homogeneous of degree 0. Moreover, HLM assume that $a(\pi)$ is a constant, which implies that the indirect group utility function is homothetic and that the second term on the right hand side of (3) can be ignored.[2] The function $b(\pi)$ in Gorman's polar form is the group price index. Information about the value of this index is sufficient (in the homothetic case (b) as well as in the in general non-homothetic case (a) when $a(\pi)$ is not a constant) to carry out the first stage of the budgeting procedure.

The two stage procedure implies that a group of commodities can be treated as if it were a single commodity with price $b(\pi)$. The number of units consumed of this aggregate commodity, denoted as q_M, would then be equal to:

$$q_M = y_M / b(\pi). \tag{4}$$

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[1] We refer to Deaton and Muellbauer (1980) for an elaborate discussion of separability and two-stage budgeting. The discussion here is restricted to the issues that are relevant for the present paper.

[2] When *a* does not depend on the prices π, the direct group utility function U_M can be written as $U_M = U^*(q) + a$, and *a* 1can be incorporated in the function *u*.

It should be noted that in general this aggregate commodity is purely imaginary and that, in general, q_M is not identical to the number of units consumed of the various commodities in the group.
After substitution of the indirect group utility function for the direct one, the utility function (1) can be rewritten as:

$$\begin{aligned} u &= u(x, V_M(y_M, \pi)) \\ &= u(x, q_M + a) \end{aligned} \tag{5}$$

where the second line uses the assumption that the group utility function satisfies Gorman's polar form with $a(\pi)$ is a constant and expresses indirect utility in terms of the aggregate commodity.
The expression in the second line of (5) can be interpreted as an ordinary utility function that has the quantity consumed of the aggregate good as its argument instead of the separable group of goods. In order to find the optimal budget for the group M, this utility function is maximized under the budget constraint (2), which can conveniently be rewritten as:

$$px + b(\pi)q_M = y. \tag{6}$$

The optimal quantity q_M that follows from this maximization should be multiplied by the price index $b(\pi)$ in order to find the optimal budget for museum visits.
HLM use this two stage model. In particular, they adopt the following specification of $b(\pi)$:[3]

$$b(\pi) = \ln\left(\sum_{m\in M} \exp(\gamma\pi_m)\right)/\gamma. \tag{7}$$

This leads to the following demand equation for visits to museum *m*:

$$\begin{aligned} q_m &= \frac{y_M}{b(\pi)} \frac{e^{\gamma\pi_m}}{\sum_{k\in M} e^{\gamma\pi_k}} \\ &= q_M \frac{e^{\gamma\pi_m}}{\sum_{k\in M} e^{\gamma\pi_k}} \end{aligned} \tag{8}$$

The first line of (8) applies Roy's identity to Gorman's polar form (3), taking into account that $a(\pi)$ is a constant and using (7) as the specification of $b(\pi)$. The second line uses (4).
This equation is remarkable, since it suggest the possibility of decomposing the demand for trips to a particular museum as the product of the total number of trips to museums and the probability that museum *m* is chosen as the actual destination.[4] It is easy to verify that $\sum_m q_m = q_M$, which shows that in this case q_M *is* equal to the total number of museum trips. The number of visits to museum *m* is therefore written as the product of the total number of museum trips and the probability that destination *m* will be chosen. Moreover, the expression for destination choice is the familiar logit model.[5] The econometric consequence of the two stage procedure that (apparently) leads to (8) is that it is possible to analyze the choice of a destination (which is the outcome of the second stage) independent of the choice of the number of trips. The aggregate price index *b* can be computed from the estimation results and used as an input for a separate analysis of the choice of the number of trips. This is exactly how HLM proceed.

[3] This is their equation (2.3.3) on page 12 with a change of notation: we use the symbol π (instead of *p*) for prices of individual commodities in the separable group and a suffix *m* (instead of *i*) to refer to these individual commodities.
[4] See HLM's equation (2.3.6) on page 12.
[5] HLM note that derivation of a nested logit destination choice model could be derived similarly. Indeed, derivation of any discrete choice model belonging to the GEV family would be possible.

In terms familiar in transportation analysis, (8) suggests that it is possible to provide a utility-theoretic underpinning of the separation between trip generation and trip distribution and to the practice of dealing separately with these two issues.

However, Gorman's polar form requires the function $b(\pi)$ to be homogeneous of degree 1 in the prices π. Specification (8), suggested by HLM, does not satisfy this requirement. Indeed, if all prices are multiplied by *k*, we get $b(k\pi) = \ln\left(\sum_{m\in M} \exp(\gamma k \pi_i)\right)/\gamma \neq kb(\pi)$. It must therefore be concluded that the specification proposed by HLM does not satisfy the requirements of economic theory.[6]

It is rather disappointing to have to conclude that the choice of a particular functional form for $b(\pi)$ makes HLM's empirical work strictly speaking incompatible with their theoretical framework that integrates a discrete choice (logit) and a count data model into a single utility maximizing setting. It seems natural therefore to ask whether the framework could be saved by choosing an alternative specification for $b(\pi)$. In order to see what can be done, we observe that application of Roy's identity to Gorman's polar form (3) with *a* a constant gives the number of visits to museum *m* as:

$$\begin{aligned} q_m &= \frac{y_M}{b(\pi)} \frac{\partial b(\pi)}{\partial \pi_m} \\ &= q_M \frac{\partial b(\pi)}{\partial \pi_m} \end{aligned} \qquad (9)$$

In order to be able to interpret q_M as the total number of units consumed from commodities belonging to group *M*, the quantities consumed of the individual commodities should add up to q_M. This requires that the partial derivatives of the price index *b* add up to 1:

$$\sum_{m\in M} \partial b(\pi)/\partial \pi_m = 1 \qquad (10)$$

If we can find a function *b* that is homogeneous of degree 1 *and* satisfies (10) we would be able to use the procedure proposed by HLM with an alternative destination choice model. However, it seems that the homogeneity requirement and (10) are not close friends. We have been able to find only one function that satisfies both of them:

$$b(\pi) = \sum_m b_m \pi_m \text{ with } \sum_m b_m = 1. \qquad (11)$$

Where the b_ms are constants. This is not a particularly attractive function, since it implies that the destination choice probabilities (which are equal to the partial derivatives $\partial b/\partial \pi_m$) are independent of the prices. We have been unable to find other functions that satisfy both requirements, even though we cannot exclude their possible existence. Appendix A contains a brief discussion of the possibility to use other GEV models than the logit in a modified HLM procedure. It is concluded there that the most popular modes, such as nested logit, are incompatible with a homogeneous of degree one function *b*. In the next subsection we will therefore consider an alternative procedure.

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[6] Note that it doesn't help to interpret π as a vector of real prices (that result, for instance, after dividing through a numéraire). In that case y_M must be interpreted as the real budget for museum trips. Maximization of the group utility function under the group budget constraint then implies that indirect group utility is homogeneous of degree 0 in the real prices of museum visits and the real budget. The function *b* should therefore be homogeneous of degree 1 in the real prices.

2.2 An alternative two-stage procedure

The concept of separability of the (direct) utility function and the associated two stage procedure are well known and have many applications in economics. However, it is also known that other forms of two stage budgeting exist that use alternative restrictions on preferences, see e.g. Deaton and Muellbauer (1980) for a discussion. In the present subsection we will consider one such alternative, which is based on separability of the indirect utility function.

We consider the indirect utility function of a consumer who derives utility from visiting museums and other consumption goods:

$$v = v(y, \pi, p) \tag{12}$$

where, as before, y denotes income, π the prices of visiting museums, and p the prices of other consumer goods. This indirect utility function does not presuppose any other property of this consumer's preferences than those implied by the conventional assumptions. Museum trips are an indirectly separable group of goods[7] if the indirect utility function (12) can be written as:

$$v = v'(y, p, w) \quad \text{with } w = w(\pi, y) \tag{13}$$

The indirect utility function must, of course, be homogeneous of degree zero in all prices and total expenditure. This condition is satisfied if we express all prices and expenditure relative to that of a numéraire. If we adopt this practice (as we will indeed do), the function w does not have to satisfy a homogeneity condition.

The function w can be interpreted as an aggregate price index of the commodity group museum visits. This interpretation is especially convincing if we add the following requirements:

$$w(\pi, y) = w'(\pi) \tag{14}$$

$$\sum_i \frac{\partial w}{\partial \pi_i} = 1 \tag{15}$$

Equation (14) states that the expenditure level should not affect the value of the price index. Equation (15) implies that if all prices change by the same amount, the aggregate price will also change by that amount.[8]

In Appendix B it is shown that, on the basis of these three[9] assumptions, the demand for trips to museum m can be written as:

$$q_m = Q \,\mathrm{Pr}_m \tag{16}$$

where Q is the total number of museum trips and Pr_m is the probability that museum m will be the destination of a particular trip. Moreover:

$$Q = -\frac{\partial v'}{\partial w} \Big/ \frac{\partial v'}{\partial y} \tag{17}$$

and:

$$\mathrm{Pr}_m = \frac{\partial w}{\partial \pi_m} \tag{18}$$

Equation (17) states that the total number of museum visits can be obtained from the indirect utility function v' by applying Roy's identity, that is, by treating w as if it is the price of a single commodity. The determination of the total number of museum trips can be interpreted as the first stage in the decision procedure and, just as the Gorman-Strotz procedure, only needs information about the value of an aggregate price index, not about individual prices.

[7] See Blackorby, Primont and Russel (1978) for a discussion of indirect separability.
[8] Even though this property seems reasonable, it is unconventional.
[9] Stated in eqs. (13), (14) and (15).

Equation (18) states that destination choice is determined by the partial derivatives of the function *w*. Destination choice is the second stage in the decision procedure and requires information about the prices of individual commodities in the group.

In this alternative procedure, the function *w* plays a similar role as the function *b* in HLM's procedure. The similarity is especially apparent from (14) and (15). Note also the crucial difference: whereas *b* must be homogeneous of degree 1 in the prices, there is no such requirement for *w*.

In order to indicate the possibilities this opens for the destination choice model, it may be noted that (15) is equivalent to[10] the requirement that $\exp(w)$ is homogeneous of degree 1 in the exponentiated prices e^{π_i}. Any homogeneous-of-degree-1 function $g(x)$ can therefore be used as a starting point for specification of the function w'. A convenient choice is the 'ces' specification $g(x) = \left(\sum_i x^{\beta}\right)^{1/\beta}$ which leads to the 'logsum' formula:

$$w(\pi) = \frac{1}{\beta}\ln\left(\sum_i e^{-\beta\pi_i}\right) \qquad (19)$$

which has partial derivatives that are identical to the logit choice probabilities. Indeed, by choosing other generator functions, the present framework allows for the use of any GEV model for destinations choice.

2.3 Income effects on destination choice

It has been shown in the previous subsection that the alternative procedure, which is based on indirect separability, leads to a two-stage model that is similar to that proposed by HLM, but avoids the problematic homogeneity restriction. In this subsection we briefly discuss the possibility to introduce effects of total expenditure (or income) on destination choice into the model. The presence of such effects often seems likely in application of destination choice models, but assumption (14) excludes it. However, unlike in the HLM procedure,[11] there is no theoretical requirement in the alternative procedure that makes it impossible to introduce such effects. We will, therefore, briefly consider the consequences of relaxing assumption (14) in the present subsection.

It is shown in Appendix B that, when *w* depends on income, (18) remains unchanged, but that (17) must now be written as:

$$Q = \frac{\partial v'/\partial w}{dv'/dy} \quad \text{where} \quad \frac{dv}{dy} = \frac{\partial v'}{\partial y} + \frac{\partial v'}{\partial w}\frac{\partial w}{\partial y}. \qquad (20)$$

This means that the determination of the total number of trips now not only requires information about the aggregate price *w*, but also about the partial derivative of this price with respect to total expenditure. The two stages are therefore not so strictly separated as in the situation where (14) holds. Nevertheless, (13) and (15) still guarantee a structure in which the destination choice submodel can be estimated separately from the trip generation model.

2.4 Welfare economic analysis

What are the implications of this model with respect to the value of museums? In order to answer this question, we consider the marginal effect of a change in the value of the price π_i of museum

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[10] This is proved in appendix A.

[11] The function *b* originates from Gorman's polar form (3) and therefore can only have prices a s arguments.

i. We take the indirect utility function (13), with conditions (14) and (15) imposed as our starting point. The change in income needed to compensate for the price change is:[12]

$$dy = -\left(\frac{\partial v'}{\partial w}\Big/\frac{\partial v'}{\partial y}\right)\frac{\partial w}{\partial \pi_i}d\pi_i . \qquad (21)$$

The term between brackets on the right hand side is related to trip generation, the second to destination choice. When equation (19) is used for the composite price w, this second term is the change in the 'logsum'.
The term in brackets on the right-hand-side of (21) gives the total number of trips. For small changes in w we can write:

$$\Delta y \approx -Q\Delta w \qquad (22)$$

which shows that the welfare effect can be approximated as the product of the number of trips and the change in the composite price.
Approximation (22) is exact if the number of trips is a fixed constant. Eq. (21) shows that the number of trips is equal to 1 when $\partial v'/\partial w$ is identically equal to 1. This is the case when the indirect utility function is:

$$v' = \frac{y-w}{c} . \qquad (23)$$

with c a function of the price of the other goods, *p*. It is no coincidence that this indirect utility function can be interpreted as referring to an individual who represents a population of consumers with random utility functions that correspond to the logit model (cf. McFadden, 1981).[13]
When the number of trips is not fixed, but depends on w and/or income, (22) is not exact. The reason is that it ignores the substitution effect of a change in the price of museum visits. Since the substitution effect is always negative, the approximation overstates the total welfare effect.
An exact formulation of the compensating variation of a change in the price of museum visits can be formulated in terms of the cost function $c(u, p, w)$ associated with the indirect utility function v'. Using suffixes 0 and 1 to distinguish the two situations, the compensation variation *V* of a change in the composite price from w_0 to w_1 can be determined as:

$$V_i = c(v_0', w_0) - c(v_0', w_1) \qquad (24)$$

This formula allows one, for instance, to assess the value of a museum if the difference between situations 0 and 1 is the disappearance of one museum. It also allows for the possibility to assess the total value of museums for an actor by considering the situation in which all museums would disappear. The approximation (22) cannot be used for this purpose since disappearance of all museums is equivalent to an infinitely large price for visiting the museums, and therefore an infinitely large increase in the logsum. The cost function does not necessarily have this unrealistic property.[14]

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[12] The numerator in the expression between brackets should be written as dv'/d_y if there is an effect of income on destination choice,

[13] A generalization to a fixed number of trips that can be larger than 1 is obtained if we formulate the utility function as $v'=(y-Q^*w)/b$, with Q^* the fixed number of trips.

[14] The welfare analysis in HLM uses the product of the number of trips (taken to be constant) and the change in the logsum. This is consistent with their theoretical model if the utility function is additive in the subutility function for museum visits. It may, however, be noted that this additivity is not a necessary consequence of their model, since they assume that the function *a* in Gormans polar form is a constant. This implies effectively that they have a

3 An empirical model

It was noted in the theoretical section above that the model developed in this paper is characterized by a distinction between trip generation and trip distribution. We will therefore start with a discussion of the latter and consider later how the distribution model fits into the remainder.

3.1 Data

In this section we apply the model developed in subsection 2.2 to museum visiting behavior. Our data refer to the owners of the National Museum Card (in Dutch Museumkaart). This Museum Card is an important tool in promoting museum attendance in The Netherlands. In return for an annual fee of € 25 for adults or € 12.50 for anyone younger than 26 years, card holders get free access to 442 museums in this country; the only remaining cost per visit being the cost of traveling. At the 150 largest participating museums, card holder visits are logged electronically. These data are collected and stored on a central server to aid reimbursement to the museums. This dataset was made available to us. It contains information about the customer number, type of card (youth or adult), the museum, the date and time of the visit, and the zip codes of both museum and visitor.

Museums with missing data or that faced incidental closure were excluded. The remaining 108 museums are a representative variety in size, type of collection and location.

Using a commercial GIS database that contains travel distance and travel time by road for every zip code combination in The Netherlands, travel distance and travel time were added to the dataset for each recorded visit.

This extended dataset was used by Boter, Rouwendal and Wedel (2005). Similar to these authors, we only use the visits of one full year (2002) to exclude seasonal effects on demand.

Here, we introduce two groups of additional variables. Firstly, we add eight dummy variables to indicate the kind of collections a museum offers. The eight collection categories were provided by the Dutch National Museum Association (NMV), who also carried out the consequent classification of the 108 museums and their collections.

Secondly, we add an indicator of the card holder's income to the dataset. No personal data on income is registered in the transaction data. However, some public and commercial databases hold information on the average income per zip code area. Here, we use public data from the Dutch Central Bureau of Statistics in which income is defined as "average total income in euros after tax per earner."[15]

This dataset has the distinct advantage that it captures a wide range of different museums, locations, competitive situations and travel distances. On average, card holders made 4.3 visits to 3.3 of the 108 museums in our dataset. A preliminary analysis of the dataset reveals that within the area enclosed by average observed travel time of 44.9 minutes, the average card holder has 29.5 out of the 108 museums to choose from. The museums visited are therefore likely to reflect a real utility to the card holder.

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homothetic group utility function. Their theoretical framework therefore allows for the use of the compensating variation in a similar way as it is employed here.

[15] The data are included in the publicly available database 'CBS Wijk- en Buurtonderzoek 2001' (='Netherlands Statistics Yard and Neighborhood Survey 2001'). Average income per earner per zip code area in this database was derived from another survey held in 2000. The average value of this variable for the persons in our survey is 12.582, its standard deviation is 12.834.

One possible problem that arises when the travel cost method is applied to this data set is that not all museum visits are home-based. People may, for instance, visit a museum while they are on holiday. In such a situation the travel time between their home and the museum is not informative about the price paid for the visit. We dealt with this problem by eliminating all museum visits that have been undertaken during school holiday periods.

3.2 Specification of the trip distribution model

The basic specification of the destination choice model follows from a logsum formula that is a slight generalization of (19):

$$w(\pi) = \frac{1}{\beta}\ln\left(\sum_i e^{-\alpha_i + \beta\pi_i}\right) \quad (25)$$

The coefficients α_i reflect the attractiveness of museum *i*. In order to deal with heterogeneity among consumers, we treat the parameters as random variables, using normal distributions. That is, we specify the parameters as follows:

$$\beta = \beta_0 + \sigma_0\varepsilon_0 , \quad (26a)$$

$$\alpha_i = \alpha_{0i} + \sigma_i\varepsilon_i . \quad (26b)$$

where the εs are standard normal distributed random variables and the other symbols represent parameters that have to be estimated.

Specification (26b) assumes that the attractiveness parameters α_i are independent of each other. However, it seems likely that the preferences of museum visitors are correlated, for instance because they have a special interest in paintings from the 17-th century, or in museum that specialize in natural history. In order to take this into account, we introduce an additional component of the attractiveness parameters that reflects the common preference for a class of museums. For this purpose, we use dummies d_j that indicate to which of the 8 classes a particular museum belongs and extend (26b) to:

$$\alpha_i = \alpha_{0i} + \sigma_i\varepsilon_i + \sum_{j=1}^{8}\rho_k d_k \varphi_k . \quad (26c)$$

In this equation the φs are also standard normal distributed random variables and the ρs are parameters. [16]

The group structure implied by (26c) is similar to that of a nested logit model.[17] However, the random coefficient formulation adopted here seems better suited for repeated observations of trips by the same household than the nested logit model, since it treats the preference for a particular group of museums as an individual effect.

A standard assumption in applications of the travel cost method is that there is no relation between the attractiveness of an amenity *i* as measured by the parameter α_i and the distance (or, more general the travel cost) to that amenity. In other words, the effect of distance on the number of trips is a pure distance decay effect caused by travel costs. This assumption may easily be violated in the data considered here. An important example is a museum that specializes in local or regional history, and will therefore be valued especially by the inhabitants of the town or region concerned. These people live at a relatively small distance from the museum and this introduces correlation between the attractiveness parameter α_i and the travel cost π_i. In order to

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[16] The classes are: visual arts, cultural history, maritime, natural history, visual arts, technology, anthropology, and other. The classes 'anthropology' and 'other' both have only one member. For these classes the parameter ρ_k has been set equal to 0. The number of estimated ρs is therefore equal to 6.

[17] See Train 2002, p. 159, for a discussion of the relationship between mixed logit and nested logit

deal with this effect, we extend the specification of the attractiveness parameter with a 'local interest' effect that depends on the visitor's distance to the museum:

$$\alpha_i = \alpha_{0i} + \alpha_{1i}\pi_i + \sigma_i\varepsilon_i + \sum_{j=1}^{8}\rho_k d_k \varphi_k \ . \tag{26d}$$

where the α_{1i}s are additional parameters to be estimated.

As a consequence of this extended specification, an identification problem arises. Substitution of (26e) and (26a) in (25) reveals that the parameter β_0 can no longer be estimated separately. We can only estimate $(\alpha_{1i} + \beta_0)$ and will therefore treat this sum as a single parameter when estimating the model. In the presence of a 'local interest effect' α_{1i} and β_0 are both negative. Estimation of this mixed logit model proceeds by simulated maximum likelihood.

3.3 Specification of the trip generation model

For our trip generation model we use the following specification of the utility function v':

$$v' = \frac{y^{1-\theta}}{1-\theta} - \frac{1}{\eta} e^{\gamma+\eta w'} \tag{27}$$

Application of Roy's identity gives:

$$Q = \exp(\gamma + \eta\, w' + \theta \ln(y)). \tag{28}$$

This loglinear specification is convenient for the count data model that we use.

In order to allow for differences between the observed number of museum visits x and the predicted number Q, we use the negative binomial model. It gives the probability $f(x)$ of observing x trips as:

$$f(x) = \frac{\Gamma(x+\lambda^{-1})}{\Gamma(\lambda^{-1})\Gamma(x+1)} (\lambda Q)^x (1+\lambda Q)^{-(x+\lambda^{-1})} \quad , x = 0,1,2,... \tag{29}$$

where $\Gamma(.)$ denotes the gamma function. The random variable x has expectation Q. The parameter λ reflects so-called overdispersion in comparison with the Poisson distribution.[18] The latter distribution is simpler and therefore more convenient. However, it has the restrictive property that its variance and mean are equal, which is often rejected in empirical data. The negative binomial has an additional parameter that allows the variance to differ from the mean. This model approaches the Poisson model when $\lambda \to 0$ (see, for instance, Cameron and Trivedi, 1998).

In estimating the model, we have to take into account that we only have information about households who visited at least one of the 108 museums during the observation period. This means that counts are truncated at the value zero. We therefore have used the conditional distribution $f(x)/(1-f(0))$, $x = 1,2,3,...$ as the basis for our likelihood function.

The likelihood is a function of the parameters γ, η, θ and λ, which have to be estimated. A complication occurs because one of the arguments of Q is w', which is a function of the random variables ε and φ, and is therefore itself a random variable. Taking this randomness into account implies that we should integrate the likelihood function over the distribution of w. More specifically, if we denote the likelihood of an observation conditional on a particular value of w as $\ell(\gamma,\eta,\theta,\lambda \mid w)$, the unconditional likelihood is:

$$\int l(\gamma,\eta,\theta,\lambda \mid w) h(w) dw \tag{30}$$

where h is the probability density function of w.

[18] Measurement error in a regressor (such as income in the data considered here) also gives rise to overdispersion. See chapter 10 of Cameron and Trivedi (1998).

Since w is a relatively complicated function of the underlying variables ε and φ that are the reason for its randomness, we used simulation to obtain random draws from the distribution h and used these to approximate the integral (30).[19]

3.4 Incorporating income effects in the destination choice model

The museum choice model can be made income dependent by respecifying attractiveness and distance decay as:

$$\beta = \beta_0 + \beta_1 y + \sigma_0 \varepsilon_0 , \tag{31a}$$

$$a_i = a_{0i} + a_{1i}\pi_i + a_{2i}\ln(y) + \sigma_i \varepsilon_i + \sum_{l=1}^{8} d_{i,l}\rho_l \varphi_l . \tag{31b}$$

Estimation of the destination choice model proceeds in the same way as for the model without income effects.

The incorporation of income effects in the destination choice model also has consequences for the count data model that explains the total number of trip. Applying (20) to indirect utility function (27) while taking into account the dependence of w on income gives:

$$\ln(Q) = \gamma + \eta w + \theta \ln(y) + \ln\left(1 + \exp(\gamma + \eta w + \theta \ln(y)) \frac{\partial w}{\partial y}\right). \tag{32}$$

This equation is more complicated than (28). It is not loglinear in the parameters to be estimated. Moreover, the appearance of the partial derivative $\partial w / \partial y$, forces us to simulate the distribution of this random variable as well.

4 Estimation results

4.1 Trip distribution model

We started with estimating the standard logit model with deterministic coefficients and an equal distance decay parameter for all destinations and subsequently introduced the generalizations discussed in 3.2 and the income effects. All models, except the first one, are estimated by maximum simulated likelihood. We used 114x250 independent draws[20] from the standard normal distribution for each household in the sample. Complete estimation results are available from the authors upon request. Table 1 gives the loglikelihood of the models that have been estimated.

Table 1 Estimation results for the trip distribution model

Model	Loglikelihood	#coeff
Basic model (standard logit)	-836,067.59	108
+ Random parameters	-799,362.76	216
+ Correlated attractiveness	-797,963.55	222
+ Different distance decay parameters	-743,404.60	329
+ Income dependent destination choice and distance decay	-743,288.08	437
Number of museum visits (school holiday periods excluded)	245,020	
Number of card holders in sample	69,643	

[19] We used the information that the destination choices of a visitor gives us about the values of the random variables by using their posterior probability densities (see Train, 2002, chapter 11, for a discussion of the method).
[20] There are 114 random coefficients, so we have 250 independent draws for each coefficient.

The table shows that taking into account the possible heterogeneity among museum visitors by using the mixed logit model implied by (26a) (26b) leads to a substantial improvement of the model. Allowing for correlated attractiveness by using (26c) instead of (26b) again increases the loglikelihood substantially. Only 6 additional parameters have been estimated since two of the eight classes of museums that were distinguished have only one member. Allowing for correlation between the distance to a museum and the value attached to it using (26d), results in a substantial further improvement of the loglikelihood. Finally, we introduced income effects by employing equations (31) in the mixed logit specification. Here, the results are somewhat ambiguous: a *t*-test shows that many of the coefficients referring to income are not significant and the increase in the value of the loglikelihood is less dramatic. However, a likelihood ratio test indicates that addition of the income coefficients is worthwhile and we therefore choose the model incorporating these income effects as our preferred specification. In the remainder of this subsection we discuss some of the results.

Distance decay effects

The distance decay parameters $(\beta_0 + \alpha_{1i})$, reflect the sum of a 'pure' distance decay effect and relation between an actor's distance to a museum and the value attached to it, caused, for instance, by a 'local interest' effect. When estimating the model we found that inclusion of this effect leads to a substantial improvement in the loglikelihood of the model. Table 2 shows that there is considerable variation in the 'gross' distance decay effect that is measured by the estimated coefficients $(\beta_0 + \alpha_{1i})$.

The first panel of Table 2 gives the 10 museums with the strongest distance decay effects. With the exception of the Railway Museum, these are indeed museums with collections that focus on a particular town or region, and therefore have a clear local interest.

The second panel gives the parameters of 5 museums which clearly have a national interest. Three of these are well known Amsterdam museums, one other is a Rotterdam museum, all specializing in visual arts, the fifth is a museum in Enkhuizen specialized in cultural history that is a popular destination for day trips. One expects that for these museums there is not much correlation between someone's location and his or her appreciation for the museum and that the estimated distance decay parameter will therefore reflect a pure effect of distance. These five museums indeed have a distance decay effect that is much smaller than the 10 highest, which confirms our expectation. However, the estimated effects for these five museums still show significant differences, both in a statistical and economic sense. For no obvious reason the Van Gogh museum has a much lower distance decay parameter than the other four in this group, suggesting that the collection of this museum is especially appreciated outside the Randstad.

The ten museums with the lowest distance decay effect are listed in the bottom panel of Table 2. Most of them are museums that specialize in a topic of general interest such as the history of baking or shipping, but there are also some that specialize in the history of a province or region. All of them are located outside the Randstad, most of them in areas that are often used as destination for a short vacation.[21] One possibility, therefore, is that the low gross distance decay

[21] Kerkrade and Maastricht are in the southern part of Limburg, Hattem and Apeldoorn at the Veluwe; both regions are popular destinations for short holidays.

effect is the result of incomplete elimination of the trips that are made from other locations than the household residence.

Table 2 Some estimated distance decay parameters

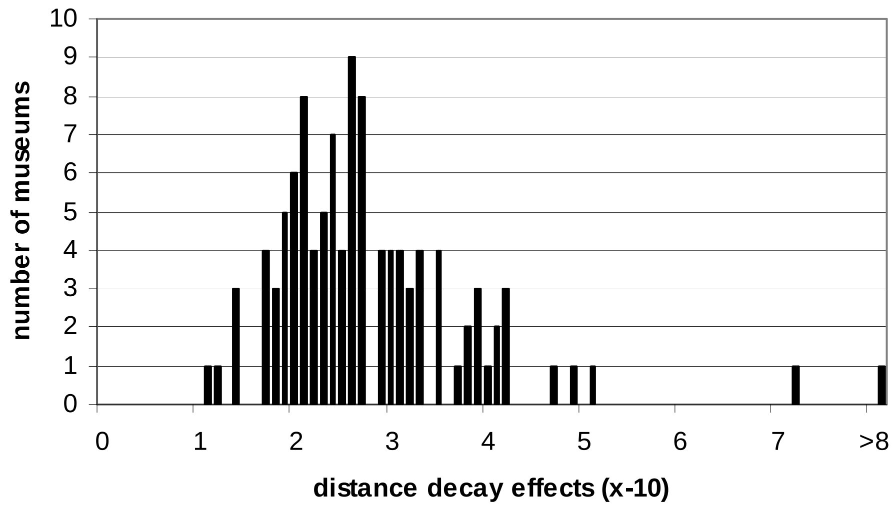
Museum	Location	Dist decay
10 highest distance decay effects		
Mill Museum	Koog a/d Zaan	-14.17
Regional Museum	Krimpen a/d Ijssel	- 7.20
Hortus Botanicus	Leyden	- 5.11
Town Mill Museum	Leyden	- 4.96
University Museum	Utrecht	- 4.79
Railway Museum	Utrecht	- 4.30
Resistance Museum	Amsterdam	- 4.26
Zaans Museum	Zaandam	- 4.22
Museum Beeckestein	Velsen-Zuid	- 4.19
Groeneveld Castle	Baarn	- 4.14
5 Museums with a national interest		
Rijksmuseum	Amsterdam	- 2.48
Van Goghmuseum	Amsterdam	- 1.95
Town Museum	Amsterdam	- 2.73
Zuiderzee museum	Enkhuizen	- 2.76
Boijmans van Beuningen	Rotterdam	- 2.42
10 lowest distance decay effects		
Groningen Museum	Groningen	- 1.16
Dutch Bakery Museum	Hattem	- 1.28
Toys and Tin Museum	Deventer	- 1.44
Bonnefantenmuseum	Maastricht	- 1.46
Industrion	Kerkrade	- 1.47
Princessehof	Leeuwarden	- 1.71
Loo Palace	Apeldoorn	- 1.74
Frisian Museum	Leeuwarden	- 1.76
Historical Museum	Deventer	- 1.77
Northern Shipping Museum	Groningen	- 1.84

The complete frequency distribution of the estimated gross distance decay effects $(\beta_0 + \alpha_{1i})$ is shown in Figure 1. The distribution is skewed and a main reason for this skewness seems to be the local interest effects associated with some museums. The frequency distribution does not have a clear mode. There are 8 museums with a distance decay parameter in the interval (-2.3,-2.2), 9 in the interval (-2.7,-2.6) and 8 in the interval (-2.8,-2.7). The median gross distance decay effect is equal to -2.65.

We have selected the distance decay parameter of the Rijksmuseum (which is equal to - 2.48), as the best approximation of the pure distance decay effect β_1. The Rijksmuseum is the Dutch national museum ‘par excellence,’ which makes it unlikely that a local interest effect is present or that other relations between the value attached to this museum and the distance to it are present. Moreover, Amsterdam and its vicinity are not a typical holiday destination for Dutch people, which makes it unlikely that this coefficient has been biased by non-home based trips.

Thus far, nothing has been said about the effect of income on the distance decay parameter. However, we can be brief about it, since β_1 turned out to be small and insignificant. There is, however, significant heterogeneity in the distance decay effect. The estimate for the standard deviation σ is approximately equal to 1.

Figure 1 Frequency distribution of estimated coefficients for distance decay and local interest



Note: the museum that has been located to the right of 8 on the horizontal axis actually has a parameter that is equal to –14.17 (see Table 2).

Attractiveness

The attractiveness of museums is indicated by the parameter α_m. However, in economic geography and transportation analysis it is more common to use $A_m = \exp(\alpha_m)$ as the attractiveness variable and we will follow this practice here. An important reason for doing so is that the number of trips to a museum is approximately proportional to its attractiveness A_m, which makes it easy to interpret. In spatial interaction analysis trips are usually thought to be generated by accessibility, here denoted as A, which is defined as the sum of the attractiveness of the various possible destinations, multiplied by a distance decay effect, that is as:

$$A(\pi) = \sum_i A_i \exp(\beta\pi_m) \tag{33}$$

Accessibility can easily be related to the logit model when it is observed that it is equal to the expression in brackets in the logsum (24):

$$w(\pi) = \ln(A(\pi)) \tag{34}$$

The mixed logit specification that we use here, implies that attractiveness A_i of a museum is a lognormal distributed variable. Table 3 gives the expected values of the attractiveness of the 20 museums with the highest scores on these variables.[22] In order to compute them, several decisions had to be taken. The parameter a_{1i}, representing the effect of a correlation between the value attached to a museum and the distance to that museum, was computed by subtracting the

[22] The computation uses $E(A_i)=\exp(a_{0i}+a_{1i}\pi^{av}+a_{2i}\ln(y^{av})+.5(\sigma_i+\Sigma\rho_l d_{i,l})^2)$ where the superscript *av* is used to denote sample averages. The determination of a_{1i} is discussed in what follows.

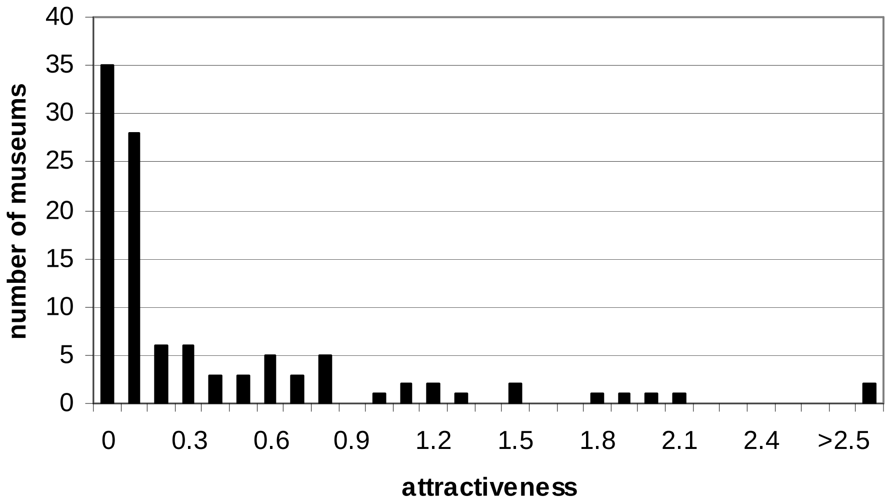
'pure' distance decay effect (β_0=-2.48), whose value was discussed in the previous subsection, from the estimated gross distance decay parameter $(\beta_0 + a_{1i})$. We computed the attractiveness of museums for visitors with a trip length of 44.9 minutes, the average travel time for a museum visit when undertaken from the residential location. Income was set to its average value. Perhaps somewhat surprisingly, the first place is occupied by the Town Museum of Amsterdam, while the Rijksmuseum, which is better known, at least among foreigners, only takes the second place. The Rijksmuseum has a larger basic attractiveness parameter a_0, but the heterogeneity parameter for the Town Museum is much larger. Moreover, there is a relatively large and significant effect of income on the attractiveness of the Town Museum, and none on the attractiveness of the Rijksmuseum.

A large share (50%) of the top twenty museums specialize in visual arts, i.e. paintings and sculptures, whereas only four of them belong to the much larger group of museums focusing on cultural history. The group of museums specializing in natural history is also well represented with 3 of its members in the top 20; two of these museums are located in Leyden. Even though the Hortus Botanicus (the University Botanical Garden) in this town has a large local interest component (see Table 2), its attractiveness remains substantial for those who have to travel three quarters of an hour. The Railway Museum is another member of the top twenty group that has a substantial local interest component in its attractiveness. Together with the Architecture Museum it represents the group of technology museums in the top 20.

Table 3 The 20 museums with highest attractiveness

Name	Location	Group	Attractiveness
Town Museum	Amsterdam	Visual arts	6.90
Rijksmuseum	Amsterdam	Visual arts/Cultural history	5.89
Groningen Museum	Groningen	Visual arts/Cultural history	3.23
Municipal Museum	The Hague	Cultural history	2.40
Naturalis	Leyden	Natural history	2.18
Cobra Museum	Amstelveen	Visual arts	2.06
Van Gogh Museum	Amsterdam	Visual arts	1.96
Singer Museum	Laren	Visual arts	1.86
Bonnefanten	Maastricht	Visual arts	1.75
Boijmans van Beuningen	Rotterdam	Visual arts	1.59
Hortus Botanicus	Leyden	Natural history	1.56
Mauritshuis	The Hague	Visual arts	1.35
Tropical Museum	Amsterdam	Anthropology	1.24
Zuiderzee Museum	Enkhuizen	Cultural history	1.19
Railway Museum	Utrecht	Technology	1.16
Loo Palace	Apeldoorn	Cultural history	1.05
Ecodrome	Zwolle	Natural history	1.01
Frisia Museum	Hoorn	Visual arts	0.90
Dutch Architecture Museum	Rotterdam	Technology	0.88
Historical Museum	Amsterdam	Cultural history	0.81

Figure 2 Frequency distribution of estimated attractiveness of museums



Note. The two museums that have been located to the left of the value 2.4 on the hrozontal axis actually have an estimated attractiveness of 5.89 and 6.90 (see Table 3).

In interpreting the figures in Table 3, it must be kept in mind that they refer to the attractiveness for a large, but specific group, namely holders of the Museum Card; Dutch people that estimate to go more than once a year to museums, as the purchase is, on average, only worthwhile when planning to visit more than three museums per year. If we had estimated a model on trips of a different group, we might have found a different ranking. For instance, it seems likely that international tourists have a higher preference for the Rijksmuseum and the Van Gogh museum, and are less acquainted with, for instance, the Zuiderzee museum, which specializes in a particular Dutch theme.

Figure 2 shows the frequency distribution of the estimated expected attractiveness of the 108 museums. The most salient feature of the figure is the large numbers of museums with a very low attractiveness and the small number of museums with a very high attractiveness. The Town Museum of Amsterdam and the Rijksmuseum have an estimated attractiveness that is more than two times as high as that of any other museum.[23] This phenomenon has been observed earlier and also in other contexts, see Frey (1998).

The effect of income on the attractiveness of many museums is small and statistically insignificant. This result may partly be due to measurement error in this variable, which was only available as an average referring to an area defined by a particular zip code. There are 12 museums with a significant positive income effect of income and 6 with a significantly negative effect. There are no obvious similarities between the museums in the group with positive or negative coefficients.

Although the results reported in Table 3 and Figure 2 are dependent on our particular choice of the 'pure' distance decay effect, they are not very sensitive to changes in the value of this parameter. For instance, choice of the median value of $\left(\beta_0 + a_{1i}\right)$, -2.65 as the pure distance

[23] This is not an artefact of our use of the lognormal distribution for heterogeneity among consumers. The phenomenon is also present in the basic logit model and appear also if we use only the parameters a_0.

decay effects does not change the set of top 20 museums, although their order is now somewhat different. Also, choice of a smaller value (up to the minimum absolute value of –1.16) does not result in substantial differences in Table 3.

Before concluding this subsection we should note that attractiveness of a museum is not identical with its value in a welfare economic sense. The welfare economic aspects of the model will be discussed in subsection 4.3.

4.2 Trip generation model

Since income effects were found to be significant in the trip distribution model, we used equation (34) for the expected number of trips. The value of the partial derivative $\partial w'/\partial y$ was determined on the basis of the estimation results reported in the previous subsection. Its value turned out to be close to zero in all cases. The reason is that the distance decay parameter does not depend on income, whereas the income effects on the attractiveness of museums are sometimes positive and sometimes negative, with the net effect on w close to zero. As a consequence, the difference between (27) and (31) is very small and ignoring the effect of income on the composite price of museums has only small effects on the results of the count data model. The results reported here refer to the model incorporating income effects in w.

Estimation results for the negative binomial model are presented in Table 4.[24] They have been obtained while taking into account the dependence of the composite price of museum trips on income. The composite price of museum visits has a significant negative effect on the number of trips. The price elasticity is equal to $\eta\pi^*$, which, on average, is equal to –1.28, indicating that demand for museum visits is price elastic. There is also a significant positive effect of income. The income elasticity of the demand for museum trips is equal to θ, suggesting that such trips are a necessity.[25] There is a significant amount of overdispersion present in our data, implying that the simple Poisson model would be inappropriate.[26] The overdispersion is reflected in the presence of a few households with a very large number of museum visits in our data.

Table 4 Estimation results for the count data model

Coefficient	Variable	Estimate	Standard error
γ	Constant	-1.76	0.27
η	Price	-0.596	0.016
Θ	Ln(Income)	0.189	0.029
λ	Overdispersion	3.582	0.102
Loglikelihood		-136,630	

4.3 Welfare economic implications

In order to assess the implications of the estimated model we use the compensating variation formula (23) and applied it to indirect utility function (26). When w does not depend on income, the result is:

[24] The standard errors reported in this table have been computed treating the estimated coefficients of the trip distribution model as constants.

[25] Note that this statement refers to the group of museums. Particular museum may be luxuries.

[26] Because our data are truncated, estimating a Poisson model would probably not result in unbiased estimates.

$$V_i = y_0 - \left(y_0^{\theta+1} - \frac{\theta+1}{\eta}\left(\exp(\gamma+\eta w_0') - \exp(\gamma+\eta w_1')\right)\right)^{1/(\theta+1)} \qquad (35)$$

When w depends on income, an analytical result can no longer be obtained. Even though numerical results can still be reached, our earlier finding that income effects on w are negligible convinced us that the error involved in using (35) would be negligible. The results reported below are therefore based on this formula. The randomness of w was taken into account by simulation in exactly the same way as when estimating the trip generation model.

Before turning to the results, we have to consider the implications of the fact that we have, until now, tacitly used travel time as the 'price' of a museum trip for computing a monetary measure of welfare. The price of a trip is the sum of a) the value of the travel time involved, and b) the price of a ticket or of fuel and maintenance of the car. For the value of time (*vot*) 7.5 euros per hour is generally regarded as an acceptable approximation in the Netherlands. The ticket price per hour in public transport is highly dependent on the type of transport and in particular on travel speed. For an intercity train service it is much lower that for a bus in the center of a city like Amsterdam. The price for car use is dependent on car type and driving conditions. In order to find a general indicator we have looked at the maximum compensation for travel costs that was acceptable for tax authorities in 2002.[27] This figure equaled 0.15 euro per kilometer traveled and it is sufficient to cover the variable cost of driving for most (if not all) car types. We used 50% of this value as our estimate of travel cost per hour and assumed an average speed of 60 kilometers per hour. This implies that we approximate monetary travel cost as 4.5 euro per hour. Total travel cost is therefore (7.5+4.5=)12 euro per hour. The travel time used in our data base is that of a single trip, so we multiplied the figure by 2 to arrive at the full travel cost of 24 euros for visiting a museum at a distance of one hour traveling from one's residential location.

The distance decay parameter is based on travel time and it must therefore be interpreted as the product of the travel cost per unit of time and a distance decay parameter that refers to the monetary travel cost. The composite price w also refers to travel time when computed on the basis of the estimated coefficients, and should, therefore, be multiplied by the monetary travel cost per unit of time in order to find the associated monetary value.

Since we used the composite price based on travel time when estimating the count data model, the estimated value of the parameter η must also be interpreted as the product of the monetary travel cost per unit of time and the price parameter that refers to a monetary price. This has been taken into account by switching to the monetary travel cost before making the computations based on (35) which are reported below.

Table 5 gives the compensating variation of a selected set of museums. The basis of the computations is the removal of one museums from the total set of available museums. The new (higher) value of w for the remaining 107 museum is then computed and the compensating variation of this change is determined.

The figures in this table are averages over all households in the sample. Column 1 reports the compensating variation of disappearance of the museum as given in (38). The table indicates, for instance, that disappearance of the Town Museum of Amsterdam would result in a loss of consumer welfare that can on average be compensated by an increase in income of almost 1.24 euros. The compensating variations computed for the other museums are of the same order of magnitude. These values are perhaps smaller than one would expect. One important reason is that

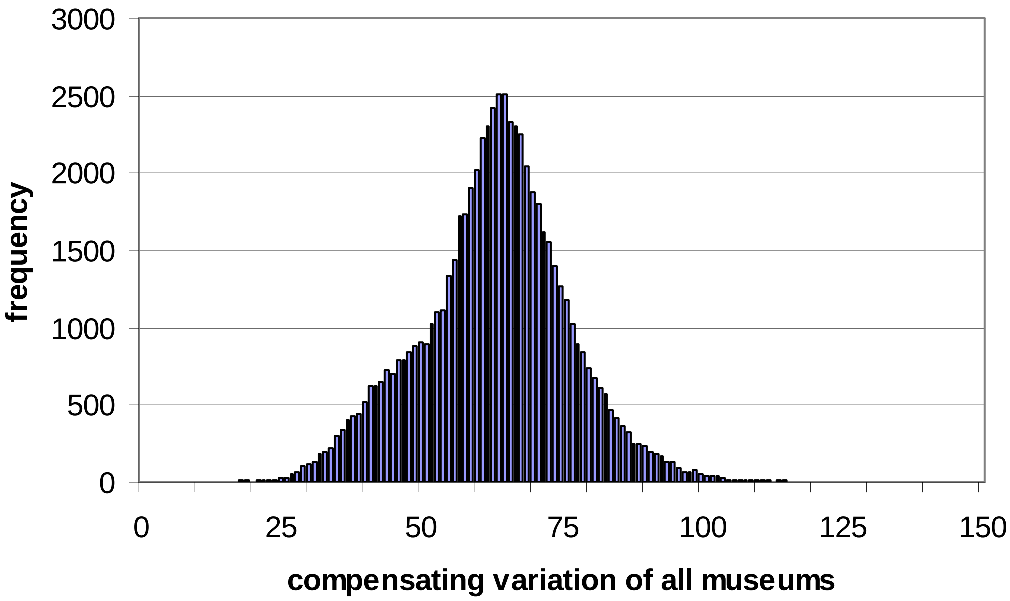
[27] If an employer would give more compensation to an employee who traveled for business purposes, the additional amount is treated as (taxable) income.

there are many museums and that they appear to be good substitutes. This seems especially to be the case for the Naturalis museum, which was ranked third on the basis of its attractiveness, but has a much lower compensating variation than the Van Gogh Museum and Groningen Museum that have a lower attractiveness. The disappearance of any single museum, including that with the highest attractiveness, would apparently not imply a substantial loss in consumer welfare.

Table 5. Values of selected museums

Museum	1 Compensating variation	2 Δ logsum * predicted # visits	3 Δ Predicted # visits
Town Museum	-1.24	-1.30	-0.03
Rijksmuseum	-1.63	-1.68	-0.04
Groningen Museum	-1.36	-1.46	-0.04
Naturalis	-0.37	-0.38	-0.01
Van Gogh Museum	-0.88	-0.89	-0.02

Figure 3 Frequency distribution of the compensating variation of all museums



The ranking of the museums on the basis of the compensating variation associated with their disappearance differs from that based on attractiveness. The Rijksmuseum and the Van Gogh museum are now both valued higher than the Amsterdam Town Museum. This reversal is related to the local interest effect of the Town Museum, which gives the other two museums a higher value for visitors outside the Randstad. The high score of the Groningen Museum, is partly explained partly by its relatively low (in absolute value) distance decay parameter, but also by the lack of good substitutes in the northern part of the country.
Column 2 of Table 5 shows the product of the predicted number of visits for the 108 museums and the change in the logsum term. This measure ignores the effect of the disappearance of the

museum on the number of trips, but is otherwise comparable to the compensating variation. Since the change in the number of trips induced by the disappearance of a single museum is small, as shown in column 3, the difference between this approximate welfare indicator and the compensating variation is small.

Figure 3 shows the frequency distribution of the expected values of the compensating variation of all museums for the persons in our sample. The lowest expected value is equal to 12, the highest to 187. For the large majority (more than 99.8%) the value of the museums is higher than the 25 euros they have to pay for the seasonal ticket, as should be expected.[28] The mode of the distribution occurs at 64 euros, and the mean equals 63 euros. It should be noted that the possibility to compute this compensating variation of all museum is directly related to our use of a model of trip generation and distribution. The logsum measure that uses only information from destination choices would suggest an infinitely high value of museum visits taken as a group, since it disregards the possibility to substitute other commodities for museum visits when their price goes up.

5 Conclusion

In this paper we have developed and estimated a model that explains the number of museum visits and their destination on the basis of a consistent utility maximizing framework. The model uses a similar framework as HLM, but takes a separable indirect utility function as its starting point. This allows us to avoid a difficulty that is associated with HLM's procedure and it is shown that the logit model fits more naturally in the model of the present paper.

Estimation of the model proceeds in two stages, one associated with trip generation, the other with trip distribution. The model, therefore, provides a utility theoretical underpinning of the widespread practice to study these two aspects of transportation demand more or less separately from each other. The model developed in this paper is also able to deal with effects of income on destination choice. The consistency with utility maximization allows for welfare analyses that do not only take into account effects on destination choice (as does the conventional difference in logsum analysis), but also effects on the number of trips.

The empirical application of the model concerned museum visits in the Netherlands among the group of holders of a special seasonal ticket that allows free entrance to a large number of Dutch museums. For destination choice a mixed logit model was used. An existing classification of the museums into eight groups was used to account for possible correlation between the values attached to museums with similar collections. This was found to be important empirically. We also found evidence for substantial local interest effects for some museums. Income effects were significant for some museums, but income did not appear to influence the strength of the distance decay effect.

For trips generation a count data model was used. Museum visits have a small positive income elasticity and the demand for such trips appears to be price elastic. There appears to be substantial overdispersion, which is possibly related to measurement error in the income variable.

The welfare economic analysis shows that the welfare effect of the disappearance of a museum depends on the availability of good substitutes at or close to the same destination. For this reason, the disappearance of the Rijksmuseum, which is one of the many museums in Amsterdam, is relatively small in comparison to that of the Groningen Museum, which is virtually the only large museum in the northern part of the Netherlands. Because of this 'spatial competition' effect there

[28] Note that our estimate exclude any museums visits made during school holidays and visits to other museums than the 108 included in the analysis of this paper.

is a substantial difference between the ranking of the museum based on attractivity and that based on compensating variation.

In our model the change in the logsum overestimates the total welfare effect, since it disregards the possibility to substitute other commodities for museum trips. If attention is focused on the value of a single museum, the difference between the change in the logsum and the compensating variation appears to be small. The reason is that in general there are good substitutes available for any museum in the sample. Computations of the value of all museums to the persons in our sample suggest an average of 63 euros per year, whereas the logsum suggests an infinitely high value.

Even though our application concerns a special group, the holders of a special seasonal ticket, the results are consistent with the opinion that museums are an important amenity of a city. Recent analyses that have brought the importance of consumer amenities for the attractiveness of cities to the fore include Brueckner, Thisse and Zenou (1999) and Glaeser, Kolko and Saiz (2000). If these analyses are correct, amenities - like museums – may well be an important reason for choosing a residential location in an urban area. Households that attach a high value to museums may, therefore, choose a location with good museum accessibility, probably implying that our estimates of the value of museum are downward biased. This phenomenon may partly be reflected in an effect of the presence of museums on the value of nearby housing.

Finally, it may be noted that our analysis is concerned only with the value of museums to visitors, often referred to as the 'use value'. People may also value museums for other reasons, such as the option to visit it later ('option value'), the option to preserve it for future generations ('bequest value'), or simply the fact that it is there ('existence value') (Frey 2003). Contingent valuation is often regarded as an appropriate tool for investigating such non-use values.[29]. For use values, however, travel cost methods seem more valid, as they measure revealed preferences, rather than a hypothetical willingness. As such, the few travel cost applications in this area compare bleakly with the large number of stated preference applications (Navrud and Ready 2002). We hope that the present study may contribute to remedy this state of affairs.

References

Blackorby, C., D. Primont and R. Russell (1978) *Duality, Separability and Functional Structure*, New York, American Elsevier.

Boter, Jaap, Jan Rouwendal and Michel Wedel (2005), "Employing Travel Time to Compare the Value of Competing Cultural Organizations," *Journal of Cultural Economics*, forthcoming.

Brueckner, J.K., J.F. Thisse and Y. Zenou (1999) Why is Central Paris Rich and Downtown Detroit Poor? An Amenity-based Theory. *European Economic Review*, **43**, 91-107.

Cameron, A.C. and K. Trivedi (1998) *Regression Analysis of Count Data*, Cambridge University Press, Cambridge.

Clawson, M. (1959) *A Method for Measuring the Demand for, and the Value of Outdoor Recreation*, Resources for the Future, Washington (DC).

Clawson. M. and J.L. Knetsch (1966) *Economics of Outdoor Recreation*, Johns Hopkins, Washington (DC).

Eurobarometer (2002), *Europeans' Participation in Cultural Activities*. Eurostat, Brussels/Strasbourg. (Available at http://europa.eu.int/comm/public_opinion/archives/eb/

[29] Tohmo, 2004, is a recent example referring to a local museum

ebs_158_en.pdf)
Forrest, David, Grime, Keith, and Woods, Robert (2000) “Is It Worth Subsidizing Regional Repertory Theatre?”, *Oxford Economic Papers* 52: 381-397.
Frey, B.S. (1998) Superstar Museums. *Journal of Cultural Economics*, **22**, 113-125.
Frey, B.S. and S. Meier (2003) The Economics of Museums, working paper 149, Institute for Empirical Research in Economics, University of Zurich. (Forthcoming in:Ginsburgh and Throsby (eds) *Handbook of Economics of At and Culture*, Elsevier.)
Glaeser, E.L., J. Kolko and A. Saiz (2000) Consumer City. *Journal of Economic Geography*
Gorman (1959) Separable Utility and Aggregation. *Econometrica*, **27**, 469-481.
Hausman, J.A., G.K. Leonard and D. McFadden (1995) A Utility-Consistent, Combined Discrete Choice and Count Data Model Assessing Recreational Use Losses Due to Natural Resource Damage, *Journal of Public Economics*, **56**, 1-30.
Johnson, P. and B. Thomas (1998) The Economics of Museums: A Research Perspective, *Journal of Cultural Economics*, **22**, 75-85.
Martin, Fernand (1994) Determining the Size of Museum Subsidies. *Journal of Cultural Economics* 18: 255-270.
McFadden, D. (1974) Conditional Logit Analysis for Qualitative Choice Behavior. In: P. Zarembka (ed.) *Frontiers in Econometrics*, Academic Press, New York, 105-142.
McFadden, D. (1981) Econometric Models of Probabilistic Choice. In: D. McFadden and C.F. Manski (eds) *Structural Analysis of Discrete Data*, MIT Press, Cambridge, 198-271.
Navrud, Ståle and Ready, Richard C. (2002) *Valuing Cultural Heritage; Applying Environmental Techniques to Historic Buildings, Monuments and Artifacts*. Edward Elgar, Cheltenham.
NEA (1998) *1997 Survey of Public Participation in the Arts* (Research Division Report # 39). National Endowment for the Arts, Washington, DC. (Available at http://arts.endow.gov/pub/ Survey/Survey.pdf)
Poor, P. Joan and Smith, Jamie M (2004) Travel Cost Analysis of a Cultural Heritage Site: The Case of Historic St. Mary’s City of Maryland. *Journal of Cultural Economics* 28: 217-229.
Strotz, R.H. (1957) The Empirical Implications of a Utility Tree. *Econometrica*, **25**, 269-280.
Tohmo, T. (2004) Economic Value of a Local Museum; Factors of Willingness-to-pay. *Journal of Socio-Economics*, 33: 229-240.
Train, K. (200.) Discrete Choice Methods with Simulation, Cambridge University Press, Cambridge.

Appendix A. The compatibility of GEV models and the HLM procedure

In this appendix we discuss the possibility that the function *b* in Gorman's polar form (3) satisfies (10). We start with a proposition.
Consider a differentiable function $b(\pi)$ from R^M to *R*. Define new variables $x_m=\exp(\pi_m)$, $m=1,\ldots,M$.

Proposition 1. $\sum_m \partial b/\partial\pi_m = 1$, if and only if $b(\pi)=\ln(g(x))$ with *g* a differentiable function that is homogeneous of degree 1 in x .

Proof. Using $d\exp(b)=\exp(b)db$ and $d\exp(\pi_m)=\exp(\pi_m)d\pi_m$ we write:

$$\sum_m \frac{\partial b}{\partial \pi_m} = \frac{1}{\exp(b)}\sum_m \frac{\partial \exp(b)}{\partial \exp(\pi_m)}.$$

Since $\sum_m \partial b/\partial\pi_m = 1$, it follows that:

$$\exp(b) = \sum_m \frac{\partial \exp(b)}{\partial \exp(\pi_m)}\exp(\pi_m).$$

Now define $g(x)=\exp(b)$ and, using the definition of x_m, rewrite this equation as:

$$g(x) = \sum_m \frac{\partial g}{\partial x_m} x_m .$$

This establishes the 'if' part.
Next, assume that $g(\rho)$ is homogeneous of degree 1 in x. Then:

$$\sum_m \frac{\partial \ln g}{\partial \pi_m} = \frac{1}{g}\sum_m \frac{\partial g}{\partial x_m} x_m .$$

The left-hand-side of this equation equals $\sum_m \partial b/\partial\pi_m$. Since *g* is homogeneous of degree 1, the right-hand-side is equal to 1. This establishes the 'only if' part.

For any generating function $G(\exp(\pi_1,\ldots,\pi_M)$ of a GEV-model the associated choice probabilities can be found as $p_i = \partial \ln G/\partial\pi_m$. Since these probabilities add up to 1, we know that (10) is satisfied if we use such a generator function for the function *g* in the proposition. Moreover, a generator function for a GEV-model must be homogeneous of degree 1 in the variables *x*.
If the function *b* is homogeneous of degree 1 in *π*, $b(k\pi)=kb(\pi)$ for any nonnegative real scalar *k*. The above proposition implies that this requirement can be reformulated as:

$$g(x)^k = g\left(x_1^k,\ldots,x_M^k\right)$$

The generator function of the multinomial logit model is: $g^{\log it}(x) = \left(\sum_m c_m x_m^{\alpha}\right)^{1/\alpha}$. Clearly, this does not satisfy the requirement for homogeneity of degree one of *b*. Many other GEV models have generating functions that are homogeneous-of-degree-one functions of the g^{logit} function. For instance, the nested logit has a generator function

$$g^{n\log it} = \left(\sum_n \left(\sum_{m\in M(n)} c_{mn} x_m^{\alpha_n}\right)^{\beta/\alpha_n}\right)^{1/\beta},$$

Where the index n refers to the nests and $M(n)$ denotes the set of destinations belonging to nest n. Clearly this function is also not compatible with a b that is homogeneous of degree 1 in π. The same conclusion follows for any other GEV model that has a generator function that is homogeneous-of-degree-one function of g^{logit} functions. Since most, if not all, existing GEV models belong to that class, it must be concluded that the possibilities to use a GEV-model for destination choice in a consistent HLM model appear to be extremely limited.

Appendix B Derivations for the procedure based on indirect separability

We take the separable indirect utility function v' in (13) as our starting point and do not impose (14) and (15). Application of Roy's identity gives:

$$q_m = \frac{\dfrac{\partial v'}{\partial \pi_m}}{\dfrac{\partial v'}{\partial y} + \dfrac{\partial v'}{\partial w}\dfrac{\partial w}{\partial y}} = \frac{\dfrac{\partial v'}{\partial w}\dfrac{\partial w}{\partial \pi_m}}{\dfrac{\partial v'}{\partial y} + \dfrac{\partial v'}{\partial w}\dfrac{\partial w}{\partial y}}$$

Total demand Q for trips to museums is then equal to:

$$Q = \sum_m q_m$$

$$= \frac{\partial v'/\partial w}{dv'/dy} \sum_m \frac{\partial w}{\partial \pi_m}$$

where $dv/dy = \partial v'/\partial y + +(\partial v'/\partial w)(\partial w/\partial y)$.

We now define the share of trips $\Pr_m$ to museum m in the total number of trips to museums as:

$$\Pr_m = \frac{q_m}{Q}$$

$$= \frac{\partial w/\partial \pi_m}{\sum_j \partial w/\partial \pi_j}$$

This equation shows that the distribution of the total number of trips over the various museums is determined solely by the function w. Moreover, it shows that the distribution of the total number of trips over the museums depends only on the real prices of museum visits, not on the prices of other goods. This is a well-known consequence of indirect separability (see Blackorby et al., 1978).

If we now impose (14), $\partial w/\partial y$ becomes 0 and we can replace dv'/dy by $\partial v'/\partial y$ in the eqation for the total number of trips Q. Imposing (15) implies that the second term on the right-hand-side in this equation becomes identically equal to 1, leaving us with eq. (17) in the main text. Imposing (15) also implies that the denominator in the expression for $\Pr_m$ becomes equal to 1, leaving us with eq. (18) of the main text.

If we impose (15), but not (14), the expression for Q becomes:

$$Q = \frac{\partial v'/\partial w}{dv'/dy},$$

and this is eq. (20) of the main text. The expression for $\Pr_m$ does not change.

Appendix C. The 108 museums

Nr	Museum	Location	Collection Category Codes
1	Groninger Museum	Groningen	Visual arts/cultural history
2	Noordelijk Scheepvaartmuseum	Groningen	Maritime
3	Museum Willem van Haren	Heerenveen	Cultural history
4	Fries Museum	Leeuwarden	Cultural history
5	Fries Natuurmuseum	Leeuwarden	Natural history
6	Princessehof Leeuwarden	Leeuwarden	Cultural history
7	Natuurcentrum Ameland	Nes Ameland	Natural history
8	Fries Scheepvaart Museum	Sneek	Maritime
9	Natuurmuseum Groningen	Groningen	Natural history
10	Museum Kempenland	Eindhoven	Cultural history
11	Stedelijk Museum Helmond	Helmond	Visual arts
12	Industrion	Kerkrade	Technology
13	Bonnefantenmuseum	Maastricht	Visual arts
14	Nederlands Textielmuseum	Tilburg	Technology
15	Natuurmuseum Brabant	Tilburg	Natural history
16	Limburgs Museum	Venlo	Cultural history
17	Stadspaleis Het Markiezenhof	Bergen op Zoom	Cultural history
18	Gorcums Museum	Gorinchem	Cultural history
19	Museum Catharina Gasthuis	Gouda	Cultural history
20	Haags Gemeentemuseum	The Hague	Cultural history
21	Museum voor Communicatie	The Hague	Technology
22	Museon	The Hague	Other
23	Nationaal Glasmuseum	Leerdam	Cultural history
24	Hortus Botanicus Leiden	Leiden	Natural history
25	Stedelijk Molenmuseum De Valk	Leiden	Technology
26	Stedelijk Museum De Lakenhal	Leiden	Visual arts
27	Zeeuws Biologisch Museum	Oostkapelle	Natural history
28	Museum Rijswijk (Het Tollenshuis)	Rijswijk zh	Cultural history
29	Mariniersmuseum	Rotterdam	Cultural history
30	Museum Boijmans Van Beuningen	Rotterdam	Visual arts
31	het Schielandshuis	Rotterdam	Cultural history
32	Zeemuseum	Scheveningen	Natural history
33	Goud-, Zilver- en Klokkenmuseum	Schoonhoven	Cultural history
34	Rijksmuseum voor Volkenkunde	Leiden	Anthropology
35	De Dubbelde Palmboom	Rotterdam	Cultural history
36	Haags Historisch Museum	The Hague	Cultural history
37	Nationaal Schoolmuseum	Rotterdam	Cultural history
38	Letterkundig/Kinderboekenmuseum	The Hague	Cultural history
39	Nederlands Architectuur Instituut	Rotterdam	Technology
40	Museum Flehite	Amersfoort	Cultural history
41	Kasteel Groeneveld	Baarn	Natural history
42	Afrika Museum	Berg en Dal	Anthropology
43	Natura Docet Natuurmuseum	Denekamp	Natural history
44	Historisch Museum De Waag	Deventer	Cultural history
45	Nationaal Bevrijdingsmuseum	Groesbeek	Cultural history
46	Nederlands Bakkerijmuseum	Hattem	Cultural history
47	Singer Museum	Laren nh	Visual arts
48	Nieuw Land Poldermuseum	Lelystad	Cultural history
49	Het Nederlands Vestingmuseum	Naarden	Cultural history
50	Museum Het Valkhof	Nijmegen	Visual arts
51	Nat. Mus. Speelklok tot Pierement	Utrecht	Technology
52	Nederlands Spoorwegmuseum	Utrecht	Technology
53	Stedelijk Museum Zutphen	Zutphen	Cultural history
54	Stedelijk Museum Zwolle	Zwolle	Cultural history
55	Speelgoed- en Blikmuseum	Deventer	Cultural history
56	Museum Schokland	Ens	Cultural history
57	Kasteel Huis Doorn	Doorn	Cultural history
58	Stedelijk Museum Alkmaar	Alkmaar	Cultural history

59	Amsterdams Historisch Museum	Amsterdam	Cultural history
60	Bijbels Museum	Amsterdam	Cultural history
61	Museum Het Rembrandthuis	Amsterdam	Visual arts
62	Joods Historisch Museum	Amsterdam	Cultural history
63	Museum Amstelkring	Amsterdam	Cultural history
64	Museum Willet-Holthuijsen	Amsterdam	Cultural history
65	Stedelijk Museum Amsterdam	Amsterdam	Visual arts
66	Theater Instituut Nederland	Amsterdam	Cultural history
67	Tropenmuseum	Amsterdam	Anthropology
68	Verzetsmuseum Amsterdam	Amsterdam	Cultural history
69	Frans Halsmuseum	Haarlem	Visual arts
70	Marinemuseum	Den Helder	Maritime
71	Molenmuseum	Koog a/d Zaan	Technology
72	Museum Beeckestijn	Velsen-zuid	Cultural history
73	Museum Nederlandse Uurwerk	Zaandam	Technology
74	Verweyhal/De Hallen	Haarlem	Visual arts
75	Rijksmuseum Amsterdam	Amsterdam	Visual arts
76	Nederlands Scheepvaartmuseum	Amsterdam	Maritime
77	Van Gogh Museum	Amsterdam	Visual arts
78	Paleis Het Loo Nationaal Museum	Apeldoorn	Cultural history
79	Museum Slot Loevestein	Poederoijen	Cultural history
80	Rijksmuseum Twenthe	Enschede	Visual arts
81	Mauritshuis	The Hague	Visual arts
82	Museum Gevangenpoort	The Hague	Cultural history
83	Museum Mesdag	The Hague	Visual arts
84	Teylers Museum	Haarlem	Technology
85	Muiderslot	Muiden	Cultural history
86	Museum Catharijneconvent	Utrecht	Cultural history
87	Museum Boerhaave	Leiden	Technology
88	Zuiderzeemuseum	Enkhuizen	Cultural history
89	Galerij Willem V	The Hague	Visual arts
90	Historisch Museum Apeldoorn	Apeldoorn	Cultural history
91	Museum voor Moderne Kunst	Arnhem	Visual arts
92	Techniek Museum Delft	Delft	Technology
93	Streekmuseum Crimpenerhof	Krimpen a/d IJssel	Cultural history
94	Universiteitsmuseum	Utrecht	Cultural history
95	Hannema-De Stuers Fundatie	Heino/Wijhe	Visual arts
96	Naturalis	Leiden	Natural history
97	Rien Poortvliet Museum	Middelharnis	Visual arts
98	Museum Kranenburgh	Bergen	Visual arts
99	Allard Pierson Museum	Amsterdam	General history
100	Museum van het Boek	The Hague	Cultural history
101	Museum van de Twintigste Eeuw	Hoorn	Cultural history
102	Natuurmuseum Rotterdam	Rotterdam	Natural history
103	Cobra Museum Amstelveen	Amstelveen	Visual arts
104	Frisia Museum, Magisch Realisme	Hoorn	Visual arts
105	Ecodrome	Zwolle	Natural history
106	Armando Museum	Amersfoort	Visual arts
107	Zaans Museum	Zaandam	Cultural history
108	Aboriginal Art Museum	Utrecht	Visual arts